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Estimates of distributions of random variables for certain computer communications traffic models

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ABSTRACT

A study of multiaccess computer communications has characterized the distributions underlying an elementary model of the user-computer interactive process. The model used is elementary in the sense that many of the random variables that generally are of interest in computer communications studies can be decomposed into the elements of this model. Data were examined from four operational multiaccess systems, and the model is shown to be robust; that is, each of the variables of the model has the same distribution independent of which of the four systems is being examined. It is shown that the gamma distribution can be used to describe each of the continuous variables of the model, and that the geometric distribution can be used to describe the discrete variables. Approximations to the gamma distribution by the exponential distribution are discussed for the systems studied.

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C.2 COMPUTER-COMMUNICATION NETWORKS

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- **D.4** OPERATING SYSTEMS
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Estimates of Distributions of Random Variables for Certain Computer Communications Traffic Models

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ABSTRACT

A study of multiaccess computer communications has characterized the distributions underlying an elementary model of the user-computer interactive process. The model used is elementary in the sense that many of the random variables that generally are of interest in computer communications studies can be decomposed into the elements of this model. Data were examined from four operational multiaccess systems, and the model is shown to be robust; that is, each of the variables of the model has the same distribution independent of which of the four systems is being examined. It is shown that the gamma distribution can be used to describe each of the continuous variables of the model, and that the geometric distribution can be used to describe the discrete variables. Approximations to the gamma distribution by the exponential distribution are discussed for the systems studied.

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Introduction

Since time sharing burst on the world some 6 or 7 years ago, many analytical studies have been published of the behavior of such systems. [1,3,7,9,13,14,15,16,20] In general, the completion of an analytical study of a real process requires several steps to be performed: construction of a process model, analysis of the model, estimation of the model parameters, and verification of the results. It is sad to report that in almost all of the published studies, the last two steps are omitted.* It is evident that the basic reasons for these omissions are (1) the difficulties encountered in the collection of necessary data due to the

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*The pioneering work of Alan Scherr[24] was of course supported by extensive measurements on the M.I.T. Project MAC CTSS System, and his results were verified by simulations. Other investigations which were supported by measurements were undertaken for the JOSS system at RAND Corp.[2,25], the Q-32 Time Sharing System at S.D.C.[6,17,18,26], and additional investigations at Project MAC[10]. Each of these investigations was performed for a specific problem for the system at hand, with no attempt at generalization. However, the results of these studies have been quoted in lieu of measurements by authors of more general studies. An excellent summary and comparisons of these investigations may be found in[23].

complexity of requisite simulations, the potential impairment of the efficiency of real systems by the measurement process, and the problem of avoiding violation of the proprietary constraints of systems applications; (2) the costs in time and dollars for conducting such studies; and (3) the questionable utility of such data in light of the rapid evolution of system capabilities and user characteristics. Nevertheless, as was first pointed out by Sackman[23] in 1967, inferences drawn from such models for the design of systems without empirical determination of parameter values and without testing of the model with the estimated parameters rest on extremely shaky foundations.

Clearly, the third reason is the most difficult to respond to. Many systems are changing so rapidly that a detailed characterization of any one will probably be outdated before it is completed. However, the architecture of computer communication systems has matured to the point that the potential for insight gained from analysis of operational systems for testing models and for forming a basis for research aimed at improvement far outweigh the drawback of obsolescence. Indeed, this situation calls for continued study and review.

If analytical models are to be of value in the design of systems, then the first two problems can be resolved. Efforts have been underway for some time at Bell Telephone Laboratories to model the user-computer interaction process in on-line multi-access computer systems as an aid in the development of new computer communication systems and services. The studies include

extensive efforts at the collection of data from representative working systems* to obtain realistic estimates of the parameters of the models. In a previous paper,[12] Jackson and Stubbs reported some of the results of these efforts; specifically, a data stream model of the interaction process was presented, together with estimates of the average values of the basic random variables of the model as obtained from measurements on working systems. In this paper, we report additional results. First, we present the results of goodness of fit tests in which standard probability density functions are fitted to the empirical estimates of the distributions of the random variables of the model. Second, we examine the significance levels of the fits for the various probability density functions and find that analytically tractable probability density functions can be used for the variables with reasonable significance levels. Third, we note a consistency between systems of widely varying types and applications in characterization of key variables and comment on the significance of this consistency.

In a small way, these analyses are analogous to the early studies of Erlang[8] and others 60-70 years ago,† in which representative examples of traffic data were collected for the

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* In every case these data are obtained on the premises of the computer service provider and with his full permission and cooperation. To ensure the privacy of the four systems under discussion, however, they are not identified by name.

† Molina[21] reports that G. T. Blood of the AT&TCo in 1898 found a close agreement between the terms of a binomial expansion and the results of the observations on the distribution of busy telephone calls. This is the earliest reference that we have been able to find to empirical studies aimed at verification of assumptions employed in telephone traffic modeling.

purpose of characterizing local and toll telephone system behavior. The Poisson arrival rate process and exponential interarrival time distribution were results of some of the earliest of these studies. It is interesting to note that the validity of these characterizations has been retained throughout the years despite the many technological changes in telephone systems and sociological changes in telephone usage.

To provide a framework for presentation of the results, we first give an overview of the study methods and review the data stream model presented in Reference [12]. We then discuss the techniques employed to characterize the variables. Finally, we present the results of the study.

Methods and Models

The modus operandi for this study is an in-depth analysis of selected multiaccess computer communication systems. These systems were selected on the basis that they are representative of the advanced state of the art, that the providers of the particular system are knowledgeable in communications, that the systems are fully operational with the initial break-in period accomplished, and that the computer service providers are willing to participate in the study. More detail on the selection procedure is given in Reference [12].

The data which are utilized in the results reported here are the detailed relationships of the flow of message characters to and from users and computers during on-line transactions. The model describes the communications process in terms

of random variables which give intercharacter times and the sizes of clusters of characters as they are transmitted through the communication interface so the raw data could be collected at the computer ports of active multiaccess computer systems. The model did not require nor did we collect data from internal computer processes such as the length of various internal queues.*

Figure 1 illustrates the data stream model. A "call" (or a connect-disconnect time period) is represented as the summation of a sequence of time periods during which the user sends characters without receiving, interleaved with time periods during which he receives characters without sending. (This implies half-duplex operation. Simple modifications to the model would allow the accommodation of full-duplex operation.) The periods during which the user is sending characters to the computer are defined as user burst segments. The periods during which he is receiving characters sent from the computer are computer burst segments. A burst segment, by definition, begins at the end of the last character of the previous computer burst segment. Similarly, a computer burst segment begins at the end

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* It is apparent that a model which portrays the interplay of the internal computer processes, such as memory management and processor time scheduling algorithms, with the communication processes would be more satisfactory for joint optimization of computer and communication performance. However, acquisition of data describing the former processes was not within the scope of this study.

of the last character sent by the user. The first burst segment of a call begins when the call is established, and the last burst segment ends when the call is terminated as measured at the computer interface.

Within a given burst segment, there are periods of line activity and of line inactivity. The first inactive period of a user burst segment is defined as think time. That is, think time is the time that elapses from the end of the last previous computer character until the beginning of the first user character in that burst segment. In most cases, think time is employed by the user to finish reading the previous computer output and to think about what to do next. The corresponding inactive period in a computer burst segment is called idle time. In some systems idle time represents time during which the user waits for the return of "line feed", after sending "carriage return"; in other systems, idle time represents the time during which the user's program is being processed or is in queue. The remaining inactive periods within a burst segment are called intercharacter times and interburst times. A prerequisite for their definition is the definition of a burst.

Two consecutive characters are defined as belonging to the same burst if the period of inactivity between the characters is less than one-half character width. Thus, each burst is the longest string of consecutive characters where the period of inactivity between any two consecutive characters is less than one-half character width. All of the characters in a burst must,

of course, be transmitted from the same party (user or computer). For example, every character of an unbroken string of characters sent at line rate is in the same burst.

For characters within the same user burst, an inactive time between two consecutive characters is called a user intercharacter time. The corresponding variable for computer bursts is computer intercharacter time. For bursts within the same user (computer) burst segment, the inactive time between two consecutive bursts is called a user (computer) interburst time. Five final variables of the data stream model are: number of user bursts per burst segment, number of computer bursts per burst segment, number of characters per user burst, number of characters per computer burst, and temporal character width (time from start to end of one character).

Collected Data and Analysis

During the study, data have been collected for a large number of transactions for each of several multiaccess computer systems. Data from four of the systems are discussed in this paper. These systems are labeled A, B, C and D. Systems A and B have the same computer equipment and basically the same mix of computer applications (scientific/engineering programming and problem solving); although the average loads supported by the two systems during the study periods were quite different. System C has computer equipment different from each of the others and its mix of user applications is oriented toward business problem solving. System D also has computer equipment different

from each of the others, and its applications are data collection and data dissemination in an inquiry/response method of operation. All four systems serve low-speed, half-duplex, teletypewriter-like terminals. Table I summarizes the salient characteristics of these systems.

TABLE I

	Systems			
	A	B	C	D
Computer Type	Brand X	Brand X	Brand Y	Brand Z
Transmission Speed (Characters/Second)	10	10	15	10
Primary Application	Scientific	Scientific	Business	Inquiry/ Response
Load*	Moderate	Heavy	Moderate	Light/ Moderate

The random variables of Figure 1 are of two types. Some are discrete, such as the number of characters per burst. Others are continuous, such as think time. Modeling techniques most commonly used in computer communications studies include queueing processes, renewal processes, birth-death models, Markov processes, and to a limited extent, flow models. Most key random parameters of models used in computer-communication studies are either inter-event times such as times between arrivals at a server or burst length counts such as the number of arrivals in a batch arrival process. In solving these types of models, only a very few random functions are tractable, and in some cases allowable. In the category of desirable functional forms fall the Poisson,

* The term load denotes the relative occupancy of the processor due to on-line demands and background batch work (if any); nothing is implied directly as to the load on the communication channel.

geometric and binomial distributions for discrete processes, and the gamma distribution family for continuous processes. Hence, we are extremely interested in the extent to which the key parameters of such models can be described by these few desirable distributions.

Data collected from the communication lines at the computer ports of the four operating systems described above were used to seek desirable distributions to describe each of the random variables of the data stream model. These data were laundered to remove ambiguities and were then partitioned into sets describing each of the variables. For each set of data for each variable for each system, goodness-of-fit tests were performed to ascertain which standard probability functions could be used to describe the variables.*

The set of distributions used for goodness-of-fit tests included the normal, Cauchy, Laplace, chi-square, exponential, hyperexponential, gamma, and lognormal distributions for continuous variables and the geometric (with and without mass at the origin), uniform, Poisson, compound Poisson and binomial distributions for discrete variables. For each variable, a compound goodness-of-fit test was performed where the parameters of the hypothesized distributions (those being tested) were adjusted so that

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* As the existing tests for goodness-of-fit were not satisfactory for our purposes because of their low power or excessive computation time, a new test was devised. This test is briefly outlined in the Appendix.

the mean and variance for a two-parameter distribution were the same as the sample mean and sample variance. For a single-parameter distribution the mean of the distribution was equated to the sample mean.

Results of the goodness-of-fit tests are shown in Table II. From the table, we see that the geometric distribution can be used to describe every discrete process but one (the single exception is an impulse function which is a degenerate form of the geometric distribution). Similarly, each of the continuous random variables of the model can be described by the gamma distribution, and the think times, idle times and interburst times can be described additionally by the lognormal distribution. These results are significant for two reasons.

First, the data stream model, which is elementary in the sense that many of the variables that generally are of interest in computer communication studies can be decomposed into the elements of the model, is shown to be robust; that is, each of the variables of the model is described by the same distribution independent of the computer system being examined.*
These results were obtained in spite of the fact that three

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* Although the truth of the statement for the "number of characters per user burst" is artificial, it is made because even for that case the same distributional form can be used in practice with no operational difficulty by chosing appropriate parameters for the distribution.

TABLE II

RESULTS OF GOODNESS OF FIT TESTS
ACCEPTABLE* DISTRIBUTIONS†

Random Variable	Systems A	B	C	D
No. of Burst Segments per Call	G	G	G	G,CP
Think Time	L,Γ	L,Γ	L,Γ	L,Γ
User Interburst Time	L,Γ	L,Γ	L,Γ	L,Γ
Computer Interburst Time	L,Γ	L,Γ	L,Γ	L,Γ
No. Bursts/User Burst Segment	G	G	G	G
No. Bursts/Computer Burst Segment	G	G	G	G
No. Characters/ User Burst	G	G	I	G,CP
No. Characters/ Computer Burst	G	G	G	G
User Intercharacter Time	Γ	Γ	N/A	Γ
Computer Intercharacter Time	Γ	Γ	Γ	Γ

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* Acceptable at the five percent level.

† Γ - gamma distribution, L - lognormal distribution G - geometric distribution, CP - compound Poisson distribution, I - Constant at X = 1.

different computer types and operating systems were investigated. In addition, the computer loads and programming applications were different. Thus, in modeling data communication systems, we can apply the analytical results from a long-holding time system to other long-holding-time systems merely by changing the parameters of the distributions. Jackson and Stubbs[12] have examined the mean values of the model variables for the first three systems and make the following observations:

1. Delays introduced by the computer (primarily idle time and computer interburst delay) can be a large component of holding time and are affected by the number of simultaneous users on the system, probably by the computer scheduling algorithm, and by the characteristics of the communications control unit.
2. The average number of characters sent by the computer to the user is an order of magnitude greater than the number of characters sent by the user to the computer.
3. Delays introduced by the user are a significant contributor to average holding time and are remarkably close in absolute values for the four systems studied.

These three observations are examples of information that may be employed by system designers in investigations into improved communications for multiaccess computers. In modeling (probabilistically) the behavior of present and proposed systems to determine their sensitivity to particular elements of the data

stream model, the parameters of the distributions need only be changed and not the distributions themselves. These data are equally valuable for investigations into computer operating systems. For example, one might investigate changes in computer scheduling algorithms as reflected in changes in idle time and interburst delay parameters, changes in transmission speed from computer to user and the converse, and changes in terminal characteristics which may influence (hopefully reduce) user delays. Indeed, recently there have been reported many investigations into the performance of scheduling algorithms as measured by response time[1,3,7,9,13,14,15,16,20]. Almost without exception, these investigations hypothesize arrival rates of requests for CPU time without the support of measurements. Since such arrivals can be approximated from the variables of the data stream model, the above observations as to the efficacy of the results reported in this paper are demonstrated.

Second, the particular distributions obtained in Table II are tractable and are useful in further analytical studies. For example, the geometric distribution was obtained for the discrete distributions and the gamma family for the continuous distributions.

Table III shows the coefficients of variation, V, for the continuous variables for the four computer systems investigated.* Since the exponential distribution belongs to the gamma distribution family and is the special case where V=1, for certain applications it may be possible to use the exponential distribution to

* For one system, the user terminal had an automatic response at the end of a computer burst segment rather than a true user "think time" response. For this system, the estimated value of V for the think time distribution was 0.72, close to that for the hyperexponential distribution (V=0.71).

describe the arrival and delay processes. To illustrate the similarity between the exponential distribution and the gamma distribution with $1.0 \leq V \leq 1.8$, Table IV is included.

TABLE III

COEFFICIENT OF VARIATION FOR GAMMA DISTRIBUTIONS

	Systems			
	A	B	C	D
Think Time	1.56	1.64	0.72	1.61
Idle Time	1.09	1.54	1.59	1.45
User Interburst Time	1.39	1.59	1.49	1.54
Computer Interburst Time	1.56	1.61	1.59	1.64
User Intercharacter Time	1.67	1.54	1.67	1.59
Computer Intercharacter Time	1.67	1.67	1.59	1.56

TABLE IV

DIFFERENCE BETWEEN CUMULATIVE DISTRIBUTIONS OF GAMMA AND EXPONENTIAL VARIATES

	Error in Percent* for Independent Variable at			
Gamma Coefficient of Variation	One-Half Mean Value	Mean Value	Twice Mean Value	Maximum Error in Tail
1.0	0.0	0.0	0.0	0.0
1.2	14.5	3.6	2.0	2.4
1.4	23.1	6.22	3.8	5.0
1.6	28.2	7.3	6.4	8.6
1.8	30.6	6.7	10.2	13.7

* With respect to gamma distribution.

The error listed in each column is the difference between the cumulative distributions at the point given. The last column lists the largest value of this error in the upper tail region. From the table, we can see that the approximation becomes less accurate as V becomes larger and is less accurate for smaller values of the independent variable than for larger ones. We further observe that even close to the origin, the class of gamma distributions defined by $V \geq 1$ has the same general shape as the exponential distribution. For much analytical work, the behavior of the distribution function in the neighborhood of the mean and in the upper tail are of the most interest. For these types of problems, if errors of the magnitudes shown in Table IV are allowable, (or alternatively if the relative coefficients of variation shown in Table III are tolerable; note that the coefficients of variations of Table III may be interpreted as relative to the exponential distribution, which has a coefficient of variation of unity) then the exponential distribution may be used in place of the gamma distribution.

Thus, assuming independent interarrivals, one can use the Poisson process to describe any of the arrival processes and have the large body of queueing theory at one's disposal to analyze the communication process of time-shared computer systems. Even for those distributions where the exponential interarrival approximation is not useful, the gamma distribution is tractable for some types of analyses.

Conclusions

In analyzing computer communication systems for time-sharing applications, the results of this work have shown that a variety of techniques can be applied to model the processes. Since the input traffic process has been characterized in terms that are usually tractable for analytical models, realistic results may be obtained using standard analytical techniques. In some models where the estimated distributional forms are not amenable to analysis, appropriate approximation techniques are available.

This work has shown that the communication process between a multiaccess computer and a user at a teletypewriter-like terminal can be represented by an elementary model from which more complex models may be constructed. Further, by using real data from operational multiaccess systems, we have shown that the model is robust and that the distributions obtained for each of the variables are tractable. In certain cases, the character arrival process can be approximated by a Poisson process. Thus, in modeling the communication process of long-holding-time multiaccess computer systems only the parameters of the distributions for the variables change for various computer types, applications and system loading.

These observations can be combined with the observations of Jackson and Stubbs[12] on computer-introduced delays, user-introduced delays and the relative amounts of information flow in each direction on the communication line to give a comprehensive

picture of the communication process. For example, these analyses support analytical and simulation studies at Bell Telephone Laboratories which seek solutions to computer access data communications problems, cf. Chu's, Meltzer's and Pilc's studies on asynchronous time division multiplexing.[4,5,19,22]

Studies of multiaccess computer communications are continuing. Data are being collected from systems with different terminal types, system configurations, average holding times, and user applications. Analyses of data for these new systems will expand our understanding of the computer-communication processes involved as we have a broader base from which to draw conclusions and make comparisons.

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APPENDIX

A Fourier Series Test of Goodness of Fit

The examination of the data for goodness of fit posed considerable problems. The objective of this part of the study was to determine the suitability of analytically tractable probability density functions (p.d.f.'s) to describe the significant random processes.

The classical goodness-of-fit tests which were first applied in this study were the chi-square test, the Kolmogorov-Smirnov test, and the Cramer-Von Mises test. These tests suffer from the following deficiencies. The power of the chi-square test is very poor, and the realized significance level is sensitive to the number and placement of class intervals. The Kolmogorov-Smirnov test and the Cramer-Von Mises test require ordering the data, which requires considerable computer time even with the most efficient algorithms for the quantities of data involved in this study.* Further, since we are interested in the suitability at an acceptable significance level of analytically tractable p.d.f.'s, the tradeoff between significance level, power, and number of sample points is of concern to us. In this regard, the only available

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* The advantage of the test used (described in the following paragraphs) over the Kolmogorov-Smirnov test or the Cramer-Von Mises test, in units of computer time, is roughly 25-50 to one.

expression for the power of the Kolmogorov-Smirnov test is a lower bound, and no expression for the power of the Cramer-Von Mises test is known at this time. An additional complication is what we need to perform a compound goodness-of-fit test where we estimate the parameters of the distribution from the data as well as testing a given distribution.

These difficulties led to the development of a new test by Jackson, called the Fourier Series Test of Goodness-of-Fit,[11] which has the following advantages:

1. No decisions about number and spacing of class intervals are required as with the construction of histograms required for the chi-square test;
2. The set of observations need not be ordered;
3. Estimators are easily updated for additions to the data base by recursive relationships which require only minimal operations on the new data;
4. The power of the test is comparable to the power of the best of the classical tests for reasonable alternatives;
5. The computation time for the Fourier test is less than the computation time for the classical tests; and

6. Using the limiting distributions, the power of the Fourier test can be computed analytically for both the simple and compound hypothesis tests, while it cannot be computed for most of the classical tests.

Briefly, the technique proceeds as follows: The probability density function is estimated from the data by a finite linear combination of sine and cosine functions harmonic over the region of support of the function - a truncated Fourier series - where the coefficients of the series are estimated from the data, and the number of terms of the series are determined by a minimization technique. Then, for each prespecified standard distribution, the hypothesis that the estimated Fourier series function is not significantly different from the Fourier series expansion of the p.d.f. of the standard distribution is tested. The test statistic used is a function of the squared differences between the coefficients of the Fourier series expansion of the estimated distribution and the coefficients of a Fourier series expansion of the hypothesized standard distribution.

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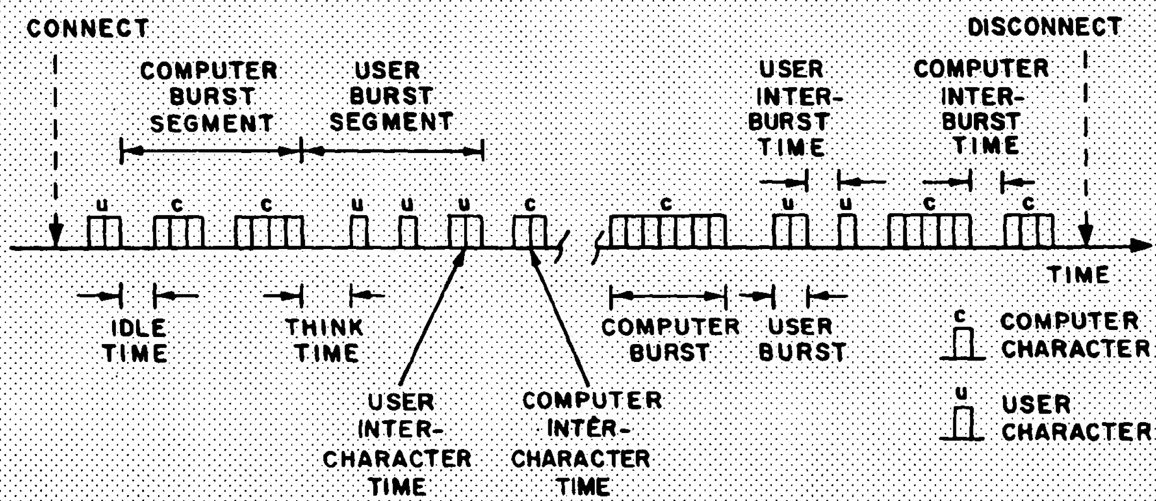

FIGURE I THE DATA STREAM MODEL

Categorizers

Distributional word clusters vs. words for text categorization

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ABSTRACT

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INDEX TERMS

Primary Classification:

H. Information Systems
H.3 INFORMATION STORAGE AND RETRIEVAL
H.3.3 Information Search and Retrieval
Subjects: Clustering

Additional Classification:

H. Information Systems
- **H.3** INFORMATION STORAGE AND RETRIEVAL
  - **H.3.1** Content Analysis and Indexing
    - **Subjects:** Indexing methods
  - **H.3.3** Information Search and Retrieval
    - **Subjects:** Search process

I. Computing Methodologies
- **I.2** ARTIFICIAL INTELLIGENCE
  - **I.2.6** Learning
    - **Subjects:** Knowledge acquisition

General Terms:
Algorithms

Collaborative Colleagues:

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Distributional Word Clusters vs. Words for Text Categorization

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Abstract

We study an approach to text categorization that combines distributional clustering of words and a Support Vector Machine (SVM) classifier. This word-cluster representation is computed using the recently introduced *Information Bottleneck* method, which generates a compact and efficient representation of documents. When combined with the classification power of the SVM, this method yields high performance in text categorization. This novel combination of SVM with word-cluster representation is compared with SVM-based categorization using the simpler bag-of-words (BOW) representation. The comparison is performed over three known datasets. On one of these datasets (the 20 Newsgroups) the method based on word clusters significantly outperforms the word-based representation in terms of categorization accuracy or representation efficiency. On the two other sets (Reuters-21578 and WebKB) the word-based representation slightly outperforms the word-cluster representation. We investigate the potential reasons for this behavior and relate it to structural differences between the datasets.

1. Introduction

The most popular approach to text categorization has so far been relying on a simple document representation in a word-based "input space". Despite considerable attempts to introduce more sophisticated techniques for document representation, like ones that are based on higher order word statistics (Caropreso et al., 2001), NLP (Jacobs, 1992; Basili et al., 2000), "string kernels" (Lodhi et al., 2002) and even representations based on word clusters (Baker and McCallum, 1998), the simple minded independent word-based representation, known as *Bag-Of-Words (BOW)*, remained very popular. Indeed, to-date the best categorization results for the well-known Reuters-21578 and 20 Newsgroups datasets are based on the BOW representation (Dumais et al., 1998; Weiss et al., 1999; Joachims, 1997).

In this paper we empirically study a familiar representation technique that is based on *word-clusters*. Our experiments indicate that text categorization based on this representation can outperform categorization based on the BOW representation, although the performance that this method achieves may depend on the chosen dataset. These empirical conclusions about the categorization performance of word-cluster representations appear to be new. Specifically, we apply the recently introduced *Information Bottleneck (IB)* clustering framework (Tishby et al., 1999; Slonim and Tishby, 2000, 2001) for generating document representation in a word *cluster* space (instead of word space), where each cluster is a distribution over document classes. We show that the combination of this IB-based representation with a Support Vector Machine (SVM) classifier (Boser et al., 1992; Schölkopf and Smola, 2002) allows for high performance in categorizing three benchmark datasets: 20 Newsgroups (20NG), Reuters-21578 and WebKB. In particular, our categorization of 20NG outperforms the strong algorithmic word-based setup of Dumais et al. (1998) (in terms of categorization accuracy or representation efficiency), which achieved the best reported categorization results for the 10 largest categories of the Reuters dataset.

This representation using word clusters, where words are viewed as distributions over document categories, was first suggested by Baker and McCallum (1998) based on the "distributional clustering" idea of Pereira et al. (1993). This technique enjoys a number of intuitively appealing properties and advantages over other feature selection (or generation) techniques. First, the dimensionality reduction computed by this word clustering implicitly considers correlations between the various features (terms or words). In contrast, popular "filter-based" greedy approaches for feature selection such as Mutual Information, Information Gain and TFIDF (see, e.g., Yang and Pedersen, 1997) only consider each feature individually. Second, the clustering that is achieved by the IB method provides a good solution to the statistical sparseness problem that is prominent in the straightforward word-based (and even more so in n-gram-based) document representations. Third, the clustering of words generates extremely compact representations (with minor information compromises) that enable strong but computationally intensive classifiers. Besides these intuitive advantages, the IB word clustering technique is formally motivated by the Information Bottleneck principle, in which the computation of word clusters aims to optimize a principled target function (see Section 3 for further details).

Despite these conceptual advantages of this word cluster representation and its success in categorizing the 20NG dataset, we show that it does not improve accuracy over BOW-based categorization, when it is used to categorize the Reuters dataset (ModApte split) and a subset of the WebKB dataset. We analyze this phenomenon and observe that the categories of documents in Reuters and WebKB are less "complex" than the categories of 20NG in the sense that documents can almost be "optimally" categorized using a small number of keywords. This is not the case for 20NG, where the contribution of low frequency words to text categorization is significant.

The rest of this paper is organized as follows. In Section 2 we discuss the most relevant related work. Section 3 presents the algorithmic components and the theoretical foundation of our scheme. Section 4 describes the datasets we use and their textual preprocessing in our experiments. Section 5 presents our experimental setup and Section 6 gives a detailed description of the results. Section 7 discusses these results. Section 8 details the computational efforts in these experiments. Finally, in Section 9 we conclude and outline some open questions.

2. Related Results

In this section we briefly overview results which are most relevant for the present work. Thus, we limit the discussion to relevant feature selection and generation techniques, and best known categorization results over the corpora we consider (Reuters-21578, the 20 Newsgroups and WebKB). For more comprehensive surveys on text categorization the reader is referred to Sebastiani (2002); Singer and Lewis (2000) and references therein. Throughout the discussion we assume familiarity with standard terms used in text categorization.[1]

We start with a discussion of feature selection and generation techniques. Dumais et al. (1998) report on experiments with multi-labeled categorization of the Reuters dataset. Over a BOW binary representation (where each word receives a count of 1 if it occurs once or more in a document and 0 otherwise) they applied the Mutual Information index for feature selection. Specifically, let C denote the set of document categories and let $X_c \in \{0,1\}$ be a binary random variable denoting the event that a random document belongs (or not) to category $c \in C$. Similarly, let $X_w \in \{0,1\}$ be a random variable denoting the event that the word w occurred in a random document. The Mutual Information between X_c and X_w is

$$I(X_c,X_w) = \sum_{X_c,X_w \in \{0,1\}} P(X_c,X_w) \log \frac{P(X_c,X_w)}{P(X_c)P(X_w)}. \tag{1}$$

Note that when evaluating $I(X_c,X_w)$ from a sample of documents, we compute $P(X_c,X_w)$, $P(X_c)$ and $P(X_w)$ using their empirical estimates.[2] For each category c, all the words are sorted according to decreasing value of $I(X_c,X_w)$ and the k top scored words are kept, where k is a pre-specified or data-dependent parameter. Thus, for each category there is a specialized representation of documents projected to the most discriminative words for the category.[3] In the sequel we refer to this Mutual Information feature selection technique as "MI feature selection" or simply as "MI".

Dumais et al. (1998) show that together with a Support Vector Machine (SVM) classifier, this MI feature selection method yields a 92.0% break-even point (BEP) on the 10 largest categories in the Reuters dataset.[4] As far as we know this is the best multi-labeled categorization result of the (10 largest categories of the) Reuters dataset. Therefore, in this work we consider the SVM classifier with MI feature selection as a baseline for handling BOW-based categorization. Some other recent works also provide strong evidence that SVM is among the best classifiers for text categorization. Among these works it is worth mentioning the empirical study by Yang and Liu (1999) (who showed that SVM outperforms other classifiers, including kNN and Naive Bayes, on Reuters with both large and small training sets) and the theoretical account of Joachims (2001) for the suitability of SVM for text categorization.

1. Specifically, we refer to precision/recall-based performance measures such as break-even-point (BEP) and F-measure and to uni-labeled and multi-labeled categorization. See Section 5.1 for further details.
2. Consider, for instance, $X_c = 1$ and $X_w = 1$. Then $P(X_c,X_w) = \frac{N_w(c)}{N(c)}$, $P(X_c) = \frac{N(c)}{N}$, $P(X_w) = \frac{N_w}{N}$, where $N_w(c)$ is a number of occurrences of word w in category c, $N(c)$ is the total number of words in c, N_w is a number of occurrences of word w in all the categories, and N is the total number of words.
3. Note that throughout the paper we consider categorization schemes that decompose m-category categorization problems into m binary problems in a standard "one-against-all" fashion. Other decompositions based on error correcting codes are also possible; see (Allwein et al., 2000) for further details.
4. It is also shown in (Dumais et al., 1998) that SVM is superior to other inducers (Rocchio, decision trees, Naive Bayes and Bayesian Nets).

Baker and McCallum (1998) apply the distributional clustering scheme of Pereira et al. (1993) (see Section 3) for clustering words represented as distributions over categories of the documents where they appear. Given a set of categories $C = \{c_i\}_{i=1}^m$, a distribution of a word w over the categories is $\{P(c_i|w)\}_{i=1}^m$. Then the words (represented as distributions) are clustered using an agglomerative clustering algorithm. Using a naive Bayes classifier (operated on these conditional distributions) the authors tested this method for uni-labeled categorization of the 20NG dataset and reported an 85.7% accuracy. They also compare this word cluster representation to other feature selection and generation techniques such as Latent Semantic Indexing (see, e.g., Deerwester et al., 1990), the above Mutual Information index and the Markov "blankets" feature selection technique of Koller and Sahami (1996). The authors conclude that categorization that is based on word clusters is slightly less accurate than the other methods while keeping a significantly more compact representation.

The "distributional clustering" approach of Pereira et al. (1993) is a special case of the general *Information Bottleneck (IB)* clustering framework presented by Tishby et al. (1999); see Section 3.1 for further details. Slonim and Tishby (2001) further study the power of this distributional word clusters representation and motivate it within the more general IB framework (Slonim and Tishby, 2000). They show that categorization based on this representation can improve the accuracy over the BOW representation whenever the training set is small (about 10 documents per category). Specifically, using a Naive Bayes classifier on a dataset consisting of 10 categories of 20NG, they observe 18.4% improvement in accuracy over a BOW-based categorization.

Joachims (1998b) used an SVM classifier for a multi-labeled categorization of Reuters without feature selection, and achieved a break-even point of 86.4%. Joachims (1997) also investigates uni-labeled categorization of the 20NG dataset, and applies the Rocchio classifier (Rocchio, 1971) over TFIDF-weighted (see, e.g., Manning and Schütze, 1999) BOW representation that is reduced using the Mutual Information index. He obtains 90.3% accuracy, which to-date is, to our knowledge, the best published accuracy of a uni-labeled categorization of the 20NG dataset. Joachims (1999) also experiments with SVM categorization of the WebKB dataset (see details of these results in the last row in Table 1).

Schapire and Singer (1998) consider text categorization using a variant of *AdaBoost* (Freund and Schapire, 1996) applied with one-level decision trees (also known as *decision stamps*) as the base classifiers. The resulting algorithm, called BoosTexter, achieves 86.0% BEP on all the categories of Reuters (ModApte split). Weiss et al. (1999) also employ boosting (using decision trees as the base classifiers and an adaptive resampling scheme). They categorize Reuters (ModApte split) with 87.8% BEP using the largest 95 categories (each having at least 2 training examples). To our knowledge this is the best result that has been achieved on (almost) the entire Reuters dataset.

Table 1 summarizes the results that were discussed in this section.

3. Methods and Algorithms

The text categorization scheme that we study is based on two components: (i) a representation scheme of documents as "distributional clusters" of words, and (ii) an SVM inducer. In this section we describe both components. Since SVMs are rather familiar and thoroughly covered in the literature, our main focus in this section is on the Information Bottleneck method and distributional clustering.

Authors	*Dataset*	*Feature Selection or Generation*	*Classifier*	*Main Result*	*Comments*
Dumais et al. (1998)	Reuters	MI and other feature selection methods	SVM, Rocchio, decision trees, Naive Bayes, Bayesian nets	SVM + MI is best: 92.0% BEP on 10 largest categories	Our baseline for Reuters (10 largest categories)
Joachims (1998b)	Reuters	none	SVM	86.4% BEP	
Schapire and Singer (1998)	Reuters	none	Boosting (BoosTexter)	86% BEP	
Weiss et al. (1999)	Reuters	none	Boosting of decision trees	87.8% BEP	Best on 95 categories of Reuters
Yang and Liu (1999)	Reuters	none	SVM, kNN, LLSF, NB	SVM is best: 86% F-measure	95 categories
Joachims (1997)	20NG	MI over TFIDF representation	Rocchio	90.3% accuracy (uni-labeled)	Our baseline for 20NG
Baker and McCallum (1998)	20NG	Distributional clustering	Naive Bayes	85.7% accuracy (uni-labeled)	
Slonim and Tishby (2000)	10 categories of 20NG	Information Bottleneck	Naive Bayes	Up to 18.4% improvement over BOW on small training sets	
Joachims (1999)	WebKB	none	SVM	94.2% - "course" 79.0% - "faculty" 53.3% - "project" 89.9% - "student"	Our baseline for WebKB

Table 1: Summary of related results.

3.1 Information Bottleneck and Distributional Clustering

Data clustering is a challenging task in information processing and pattern recognition. The challenge is both conceptual and computational. Intuitively, when we attempt to cluster a dataset, our goal is to partition it into subsets such that points in the same subset are more "similar" to each other than to points in other subsets. Common clustering algorithms depend on choosing a similarity measure between data points and a "correct" clustering result can be dependent on an appropriate choice of a similarity measure. The choice of a "correct" measure must be defined relative to a particular application. For instance, consider a hypothetical dataset containing articles by each of two authors, so that half of the articles authored by each author discusses one topic, and the other half discusses another topic. There are two possible dichotomies of the data which could yield two different bi-partitions: according to the topic or according to the writing style. When asked to cluster this set into two sub-clusters, one cannot successfully achieve the task without knowing the goal. Therefore, without a suitable target at hand and a principled method for choosing a similarity measure suitable for the target, it can be meaningless to interpret clustering results.

The *Information Bottleneck (IB)* method of Tishby, Pereira, and Bialek (1999) is a framework that can in some cases provide an elegant solution to this problematic "metric selection" aspect of data clustering. Consider a dataset given by i.i.d. observations of a random variable X. Informally,

the IB method aims to construct a relevant encoding of the random variable X by partitioning X into domains that preserve (as much as possible) the Mutual Information between X and another "relevance" variable, Y. The relation between X and Y is made known via i.i.d. observations from the joint distribution $P(X,Y)$. Denote the desired partition (clustering) of X by $\tilde{X}$. We determine $\tilde{X}$ by solving the following variational problem: *Maximize the Mutual Information* $I(\tilde{X},Y)$ *with respect to the partition* $P(\tilde{X}|X)$, *under a minimizing constraint on* $I(\tilde{X},X)$. In particular, the Information Bottleneck method considers the following optimization problem: Maximize

$$I(\tilde{X},Y)-\beta I(\tilde{X},X)$$

over the conditional $P(\tilde{X}|X)$, where the parameter β determines the allowed amount of reduction in information that $\tilde{X}$ bears on X. Namely, we attempt to find the optimal tradeoff between the minimal partition of X and the maximum preserved information on Y. Tishby et al. (1999) show that a solution for this optimization problem is characterized by

$$P(\tilde{X}|X)=\frac{P(\tilde{X})}{Z(\beta,X)}\exp\left[-\beta\sum_Y P(Y|X)\ln\left(\frac{P(Y|X)}{P(Y|\tilde{X})}\right)\right],$$

where $Z(\beta,X)$ is a normalization factor, and $P(Y|\tilde{X})$ in the exponential is defined implicitly, through Bayes' rule, in terms of the partition (assignment) rules $P(\tilde{X}|X)$, $P(Y|\tilde{X})=\frac{1}{P(\tilde{X})}\sum_X P(Y|X)P(\tilde{X}|X)P(X)$ (see Tishby et al., 1999, for details). The parameter β is a Lagrange multiplier introduced for the constrained information, but using a thermodynamical analogy β can also be viewed as an inverse temperature, and can be utilized as an *annealing* parameter to choose a desired cluster resolution.

Before we continue and present the IB clustering algorithm in the next section, we note on the contextual background of the IB method and its connection to "distributional clustering". Pereira, Tishby, and Lee (1993) introduced "distributional clustering" for distributions of verb-object pairs. Their algorithm clustered nouns represented as distributions over co-located verbs (or verbs represented as distributions over co-located nouns). This clustering routine aimed at minimizing the average distributional similarity (in terms of the Kullback-Leibler divergence, see Cover and Thomas, 1991) between the conditional $P(verb|noun)$ and the noun centroid distributions (i.e. these centroids are also distributions over verbs). It turned out that this routine is a special case of the more general IB framework. IB clustering has since been used to derive a variety of effective clustering and categorization routines (see, e.g., Slonim and Tishby, 2001; El-Yaniv and Souroujon, 2001; Slonim et al., 2002) and has interesting extensions (Friedman et al., 2001; Chechik and Tishby, 2002). We note also that unlike other variants of distributional clustering (such as the PLSI approach of Hoffman, 2001), the IB method is not based on a generative (mixture) modelling approach (including their assumptions) and is therefore more robust.

3.2 Distributional Clustering via Deterministic Annealing

Given the IB Markov chain condition $\tilde{X}\leftrightarrow X\leftrightarrow Y$ (which is not an assumption on the data; see Tishby et al., 1999, for details), a solution to the IB optimization satisfies the following self-consistent equations:

$$P(\tilde{X}|X) = \frac{P(\tilde{X})}{Z(\beta,X)}\exp\left[-\beta\sum_Y P(Y|X)\ln\left(\frac{P(Y|X)}{P(Y|\tilde{X})}\right)\right]; \qquad (2)$$

$$P(\tilde{X}) = \sum_X P(X)P(\tilde{X}|X); \tag{3}$$

$$P(Y|\tilde{X}) = \sum_X P(Y|X)P(X|\tilde{X}). \tag{4}$$

Tishby et al. (1999) show that a solution can be obtained by starting with an arbitrary solution and then iterating the equations. For any value of β this procedure is guaranteed to converge.[5] Lower values of the β parameter (high "temperatures") correspond to poor distributional resolution (i.e. fewer clusters) and higher values of β (low "temperatures") correspond to higher resolutions (i.e. more clusters).

Input:
$P(X,Y)$ - Observed joint distribution of two random variables X and Y
k - desired number of centroids
β_{min}, β_{max} - minimal / maximal values of β
$\nu > 1$ - annealing rate
$\delta_{conv} > 0$ - convergence threshold, $\delta_{merge} > 0$ - merging threshold
Output:
Cluster centroids, given by $\{P(Y|\tilde{x}_i)\}_{i=1}^k$
Cluster assignment probabilities, given by $P(\tilde{X}|X)$

Initiate $\beta \leftarrow \beta_{min}$ - current β parameter
Initiate $r \leftarrow 1$ - current number of centroids
repeat
  { *1. "EM"-like iteration:* }
  Compute $P(\tilde{X}|X)$, $P(\tilde{X})$ and $P(Y|\tilde{X})$ using Equations (2), (3) and (4) respectively
  repeat
    Let $P_{old}(\tilde{X}|X) \leftarrow P(\tilde{X}|X)$
    Compute new values for $P(\tilde{X}|X)$, $P(\tilde{X})$ and $P(Y|\tilde{X})$ using (2), (3) and (4)
  until for each x: $\|P(\tilde{X}|x) - P_{old}(\tilde{X}|x)\| < \delta_{conv}$
  { *2. Merging:* }
  for all $i, j \in [1,r]$ s.t. $i < j$ and $\|P(Y|\tilde{x}_i) - P(Y|\tilde{x}_j)\| < \delta_{merge}$ **do**
    Merge $\tilde{x}_i$ and $\tilde{x}_j$: $P(\tilde{x}_i|X) = P(\tilde{x}_i|X) + P(\tilde{x}_j|X)$
    Let $r \leftarrow r - 1$
  end for
  { *3. Centroid ghosting:* }
  for all $i \in [1,r]$ **do**
    Create $\tilde{x}_{r+i}$ s.t. $\|P(Y|\tilde{x}_{r+i}) - P(Y|\tilde{x}_i)\| = \delta_{merge}$
    Let $P(\tilde{x}_i|X) \leftarrow \frac{1}{2}P(\tilde{x}_i|X)$, $P(\tilde{x}_{r+i}|X) \leftarrow \frac{1}{2}P(\tilde{x}_i|X)$
  end for
  Let $r \leftarrow 2r$, $\beta \leftarrow \nu\beta$
until $r \geqslant k$ or $\beta \geqslant \beta_{max}$
If $r > k$ then merge $r - k$ closest centroids (each to its closest centroid neighbor)

Algorithm 1: Information Bottleneck distributional clustering

We use a hierarchical top-down clustering procedure for recovering the distributional IB clusters. A pseudo-code of the algorithm is given in Algorithm 1.[6] Starting with one cluster (very small β) that contains all the data we incrementally achieve the desired number of clusters by performing a process consisting of *annealing stages*. At each annealing stage we increment β and attempt to

5. This procedure is analogous to the Blahut-Arimoto algorithm in Information Theory (Cover and Thomas, 1991).
6. A similar annealing procedure, known as *deterministic annealing*, was introduced in the context of clustering by Rose (1998).

split existing clusters. This is done by creating (for each centroid) a new "ghost" centroid at some random small distance from the original centroid. We then attempt to cluster the points (distributions) using all (original and ghost) centroids by iterating the above IB self-consisting equations, similar to the *Expectation-Maximization (EM)* algorithm (Dempster et al., 1977). During these iterations the centroids are adjusted to their (locally) optimal positions and (depending on the annealing increment of β) some "ghost" centroids can merge back with their centroid sources. Note that in this scheme (as well as in the similar deterministic annealing algorithm of Rose, 1998), one has to use an appropriate annealing rate in order to identify *phase transitions* which correspond to cluster splits.

An alternative agglomerative (bottom-up) hard-clustering IB algorithm was developed by Slonim and Tishby (2000). This algorithm generates hard clustering of the data and thus approximates the above IB clustering procedure. Note that the time complexity of this algorithm is $O(n^2)$, where n is the number of data points (distributions) to be clustered (see also an approximate faster agglomerative procedure by Baker and McCallum, 1998).

The application of the IB clustering algorithm in our context is straightforward. The variable X represents words that appear in training documents. The variable Y represents class labels and thus, the joint distribution $P(X,Y)$ is characterized by pairs (w,c), where w is a word and c is the class label of the document where w appears. Starting with the observed conditionals $\{P(Y=c|X=w)\}_c$ (giving for each word w its class distribution) we cluster these distributions using Algorithm 1. For a pre-specified number of clusters k the output of Algorithm 1 is: (i) k centroids, given by the distributions $\{P(\tilde{X}=\tilde{w}|X=w)\}_{\tilde{w}}$ for each word w, where $\tilde{w}$ are the word centroids (i.e. there are k such word centroids which represent k word clusters); (ii) Cluster assignment probabilities given by $P(\tilde{X}|X)$. Thus, each word w may (partially) belong to all k clusters and the association weight of w to the cluster represented by the centroid $\tilde{w}$ is $P(\tilde{w}|w)$.

The time complexity of Algorithm 1 is $O(c_1c_2mn)$, where c_1 is an upper limit on the number of annealing stages, c_2 is an upper limit on the number of convergence stages, m is the number of categories and n is the number of data points to cluster.

In Table 2 we provide an example of the output of Algorithm 1 applied to the 20NG corpus (see Section 4.2) with both $k=300$ and $k=50$ cluster centroids. For instance, we see that $P(\tilde{w}_4|\text{attacking})=0.99977$ and $P(\tilde{w}_1|\text{attacking})=0.000222839$. Thus, the word "attacking" mainly belongs to cluster $\tilde{w}_4$. As can be seen, all the words in the table belong to a single cluster or mainly to a single cluster. With values of k in this range this behavior is typical to most of the words in this corpus (the same is also true for the Reuters and WebKB datasets). Only a small fraction of less than 10% of words significantly belong to more than one cluster, for any number of clusters $50 \leqslant k \leqslant 500$. It is also interesting to note that IB clustering often results in word stemming. For instance, "atom" and "atoms" belong to the same cluster. Moreover, contextually synonymous words are often assigned to the same cluster. For instance, many "computer words" such as "computer", "hardware", "ibm", "multimedia", "pc", "processor", "software", "8086" etc. compose the bulk of one cluster.

3.3 Support Vector Machines (SVMs)

The *Support Vector Machine (SVM)* (Boser et al., 1992; Schölkopf and Smola, 2002) is a strong inductive learning scheme that enjoys a considerable theoretical and empirical support. As noted in

Word	*Clustering to 300 clusters*	*Clustering to 50 clusters*
at	$\tilde{w}_{97}$ (1.0)	$\tilde{w}_{44}$ (0.996655) $\tilde{w}_{21}$ (0.00334415)
ate	$\tilde{w}_{205}$ (1.0)	$\tilde{w}_{42}$ (1.0)
atheism	$\tilde{w}_{56}$ (1.0)	$\tilde{w}_{3}$ (1.0)
atheist	$\tilde{w}_{76}$ (1.0)	$\tilde{w}_{3}$ (1.0)
atheistic	$\tilde{w}_{56}$ (1.0)	$\tilde{w}_{3}$ (1.0)
atheists	$\tilde{w}_{76}$ (1.0)	$\tilde{w}_{3}$ (1.0)
atmosphere	$\tilde{w}_{200}$ (1.0)	$\tilde{w}_{33}$ (1.0)
atmospheric	$\tilde{w}_{200}$ (1.0)	$\tilde{w}_{33}$ (1.0)
atom	$\tilde{w}_{92}$ (1.0)	$\tilde{w}_{13}$ (1.0)
atomic	$\tilde{w}_{92}$ (1.0)	$\tilde{w}_{35}$ (1.0)
atoms	$\tilde{w}_{92}$ (1.0)	$\tilde{w}_{13}$ (1.0)
atone	$\tilde{w}_{221}$ (1.0)	$\tilde{w}_{14}$ (0.998825) $\tilde{w}_{13}$ (0.00117386)
atonement	$\tilde{w}_{221}$ (1.0)	$\tilde{w}_{12}$ (1.0)
atrocities	$\tilde{w}_{4}$ (0.99977) $\tilde{w}_{1}$ (0.000222839)	$\tilde{w}_{5}$ (1.0)
attached	$\tilde{w}_{251}$ (1.0)	$\tilde{w}_{30}$ (1.0)
attack	$\tilde{w}_{71}$ (1.0)	$\tilde{w}_{28}$ (1.0)
attacked	$\tilde{w}_{4}$ (0.99977) $\tilde{w}_{1}$ (0.000222839)	$\tilde{w}_{10}$ (1.0)
attacker	$\tilde{w}_{103}$ (1.0)	$\tilde{w}_{28}$ (1.0)
attackers	$\tilde{w}_{4}$ (0.99977) $\tilde{w}_{1}$ (0.000222839)	$\tilde{w}_{5}$ (1.0)
attacking	$\tilde{w}_{4}$ (0.99977) $\tilde{w}_{1}$ (0.000222839)	$\tilde{w}_{10}$ (1.0)
attacks	$\tilde{w}_{71}$ (1.0)	$\tilde{w}_{28}$ (1.0)
attend	$\tilde{w}_{224}$ (1.0)	$\tilde{w}_{15}$ (1.0)
attorney	$\tilde{w}_{91}$ (1.0)	$\tilde{w}_{28}$ (1.0)
attribute	$\tilde{w}_{263}$ (1.0)	$\tilde{w}_{22}$ (1.0)
attributes	$\tilde{w}_{263}$ (1.0)	$\tilde{w}_{22}$ (1.0)

Table 2: A clustering example of 20NG words. $\tilde{w}_i$ are centroids to which the words "belong", the centroid weights are shown in the brackets.

Section 2 there is much empirical support for using SVMs for text categorization (Joachims, 2001; Dumais et al., 1998, etc.).

Informally, for linearly separable two-class data, the (linear) SVM computes the *maximum margin* hyperplane that separates the classes. For non-linearly separable data there are two possible extensions. The first (Cortes and Vapnik, 1995) computes a "soft" maximum margin separating hyperplane that allows for training errors. The accommodation of errors is controlled using a fixed cost parameter. The second solution is obtained by implicitly embedding the data into a high (or infinite) dimensional space where the data is likely to be separable. Then, a maximum margin hyperplane is sought in this high-dimensional space. A combination of both approaches (soft margin and embedding) is often used.

The SVM computation of the (soft) maximum margin is posed as a quadratic optimization problem that can be solved in time complexity of $O(kn^2)$, where n is the training set size and k is the dimension of each point (number of features). Thus, when applying SVM for text categorization of large datasets, an efficient representation of the text can be of major importance.

SVMs are well covered by numerous papers, books and tutorials and therefore we suppress further descriptions here. Following Joachims (2001) and Dumais et al. (1998) we use a linear SVM in all our experiments. The implementation we use is SVM*light* of Joachims.[7]

3.4 Putting it All Together

For handling m-class categorization problems ($m > 2$) we choose (for both the uni-labeled and multi-labeled settings) a straightforward decomposition into m binary problems. Although this decomposition is not the best for all datasets (see, e.g., Allwein et al., 2000; Fürnkranz, 2002) it allows for a direct comparison with the related results (which were all achieved using this decomposition as well, see Section 2). Thus, for a categorization problem into m classes we construct m binary classifiers such that each classifier is trained to distinguish one category from the rest. In *multi-labeled* categorization (see Section 5.1) experiments we construct for each category a "hard" (threshold) binary SVM and each test document is considered by all binary classifiers. The subset of categories attributed for this document is determined by the subset of classifiers that "accepted" it. On the other hand, in *uni-labeled* experiments we construct for each category a *confidence-rated* SVM that output for a (test) document a real confidence-rate based on the distance of the point to the decision hyperplane. The (single) category of a test document is determined by the classifier that outputs the largest confidence rate (this approach is sometimes called "max-win").

A major goal of our work is to compare two categorization schemes based on the two representations: the simple BOW representation together with Mutual Information feature selection (called here ***BOW+MI***) and a representation based on word clusters computed via IB distributional clustering (called here ***IB***).

We first consider a BOW+MI uni-labeled categorization. Given a training set of documents in m categories, for each category c, a binary confidence-rated linear SVM classifier is trained using the following procedure: The k most discriminating words are selected according to the Mutual Information between the word w and the category c (see Equation (1)). Then each training document of category c is projected over the corresponding k "best" words and for each category c a dedicated classifier h_c is trained to separate c from the other categories. For categorizing a new (test) document d, for each category c we project d over the k most discriminating words of category c. Denoting a projected document d by d_c, we compute $h_c(d_c)$ for all categories c. The category attributed for d is $\arg\max_c h_c(d_c)$. For multi-labeled categorization the same procedure is applied except that now we train, for each category c, hard (non-confidence-rated) classifiers h_c and the subset of categories attributed for a test document d is $\{c : h_c(d_c) = 1\}$.

The structure of the IB categorization scheme is similar (in both the uni-labeled and multi-labeled settings) but now the representation of a document consists of vectors of *word cluster* counts corresponding to a cluster mapping (from words to cluster centroids) that is computed for *all* categories simultaneously using the Information Bottleneck distributional clustering procedure (Algorithm 1).

7. The SVM*light* software can be downloaded at: http://svmlight.joachims.org/.

4. Datasets

Three benchmark datasets - Reuters-21578, 20 Newsgroups and WebKB - were experimented with in our application of feature selection for text categorization. In this section we describe these datasets and the preprocessing that was applied to them.

4.1 Reuters-21578

The Reuters-21578 corpus contains 21578 articles taken from the Reuters newswire.[8] Each article is typically designated into one or more semantic categories such as "earn", "trade", "corn" etc., where the total number of categories is 114. We used the ModApte split, which consists of a training set of 7063 articles and a test set of 2742 articles.[9]

In both the training and test sets we preprocessed each article so that any additional information except for the title and the body was removed. In addition, we lowered the case of letters. Following Dumais et al. (1998) we generated distinct features for words that appear in article titles. In the IB-based setup (see Section 3.4) we applied a filter on low-frequency words: we removed words that appear in W_{low_freq} articles or less, where W_{low_freq} is determined using cross-validation (see Section 5.2). In the BOW+MI setup this filtering of low-frequency words is essentially not relevant since these words are already filtered out by the Mutual Information feature selection index.

4.2 20 Newsgroups

The 20 Newsgroups (20NG) corpus contains 19997 articles taken from the Usenet newsgroups collection.[10] Each article is designated into one or more semantic categories and the total number of categories is 20, all of them are of about the same size. Most of the articles have only one semantic label, while about 4.5% of the articles have two or more labels. Following Schapire and Singer (2000) we used the "Xrefs" field of the article headers to detect multi-labeled documents and to remove duplications. We preprocessed each article so that any additional information except for the subject and the body was removed. In addition, we filtered out lines that seemed to be part of binary files sent as attachments or pseudo-graphical text delimiters. A line is considered to be a "binary" (or a delimiter) if it is longer than 50 symbols and contains no blanks. Overall we removed 23057 such lines (where most of these occurrences appeared in a dozen of articles overall). Also, we lowered the case of letters. As in the Reuters dataset, in the IB-based setup we applied a filter on low-frequency words, using the parameter W_{low_freq} determined via cross-validation.

4.3 WebKB: World Wide Knowledge Base

The World Wide Knowledge Base dataset (WebKB)[11] is a collection of 8282 web pages obtained from four academic domains. The WebKB was collected by Craven et al. (1998). The web pages in the WebKB set are labeled using two different polychotomies. The first is according to topic and the second is according to web domain. In our experiments we only considered the first poly-

8. Reuters-21578 can be found at: http://www.daviddlewis.com/resources/testcollections/reuters21578/.
9. Note that in these figures we count documents with at least one label. The original split contains 9603 training documents and 3299 test documents where the additional articles have no labels. While in practice it may be possible to utilize additional unlabeled documents for improving performance using semi-supervised learning algorithms (see, e.g., El-Yaniv and Souroujon, 2001), in this work we simply discarded these documents.
10. The 20 Newsgroups can be found at: http://kdd.ics.uci.edu/databases/20newsgroups/20newsgroups.html.
11. WebKB can be found at: http://www-2.cs.cmu.edu/afs/cs.cmu.edu/project/theo-11/www/wwkb/.

chotomy, which consists of 7 categories: *course*, *department*, *faculty*, *project*, *staff*, *student* and *other*. Following Nigam et al. (1998) we discarded the categories *other*,[12] *department* and *staff*. The remaining part of the corpus contains 4199 documents in four categories. Table 3 specifies the 4 remaining categories and their sizes.

Category	*Number of articles*	*Proportion* (%)
course	930	22.1
faculty	1124	26.8
project	504	12.0
student	1641	39.1

Table 3: Some essential details of WebKB categories.

Since the web pages are in HTML format, they contain much non-textual information: HTML tags, links etc. We did not filter this information because some of it is useful for categorization. For instance, in some documents anchor-texts of URLs are the only discriminative textual information. We did however filter out non-literals and lowered the case of letters. As in the other datasets, in the IB-based setup we applied a filter on low-frequency words, using the parameter W_{low_freq} (determined via cross-validation).

5. Experimental Setup

This section presents our experimental model, starting with a short overview of the evaluation methods we used.

5.1 Optimality Criteria and Performance Evaluation

We are given a training set $D_{train} = \{(d_1, \ell_1), \ldots, (d_n, \ell_n)\}$ of labeled text documents, where each document d_i belongs to a document set D and the label $\ell_i = \ell_i(d_i)$ of d_i is within a predefined set of categories $C = \{c_1, \ldots, c_m\}$. In the *multi-labeled* version of text categorization, a document can belong to several classes simultaneously. That is, both $h(d)$ and $\ell(d)$ can be sets of categories rather than single categories. In the case where each document has only a single label we say that the categorization is *uni-labeled*.

We measure the empirical effectiveness of multi-labeled text categorization in terms of the classical information retrieval parameters of "precision" and "recall" (Baeza-Yates and Ribeiro-Neto, 1999). Consider a multi-labeled categorization problem with m classes, $C = \{c_1, \ldots, c_m\}$. Let h be a classifier that was trained for this problem. For a document d, let $h(d) \subseteq C$ be the set of categories designated by h for d. Let $\ell(d) \subseteq C$ be true categories of d. Let $D_{test} \subset D$ be a *test set* of "unseen" documents that were not used in the construction of h. For each category c_i, define the following quantities:

$$
\begin{aligned}
TP_i &= \sum_{d \in D_{test}} I[c_i \in \ell(d) \wedge c_i \in h(d)], \\
TN_i &= \sum_{d \in D_{test}} I[c_i \in \ell(d) \wedge c_i \notin h(d)],
\end{aligned}
$$

12. Note however that *other* is the largest category in WebKB and consists about 45% of this set.

$$FP_i = \sum_{d \in D_{test}} I[c_i \notin \ell(d) \wedge c_i \in h(d)],$$

where $I[\cdot]$ is the indicator function. For example, FP_i (the "false positives" with respect to c_i) is the number of documents categorized by h into c_i whose true set of labels does not include c_i, etc. For each category c_i we now define the precision $P_i = P_i(h)$ of h and the recall $R_i = R_i(h)$ with respect to c_i as $P_i = \frac{TP_i}{TP_i+FP_i}$ and $R_i = \frac{TP_i}{TP_i+TN_i}$. The overall *micro-averaged precision* $P = P(h)$ and *recall* $R = R(h)$ of h is a weighted average of the individual precisions and recalls (weighted with respect to the sizes of the test set categories). That is, $P = \frac{\sum_{i=1}^m TP_i}{\sum_{i=1}^m (TP_i+FP_i)}$ and $R = \frac{\sum_{i=1}^m TP_i}{\sum_{i=1}^m (TP_i+TN_i)}$. Due to the natural tradeoff between precision and recall, the following two quantities are often used in order to measure the performance of a classifier:

- *F-measure:* The harmonic mean of precision and recall; that is $F = \frac{2}{1/P+1/R}$.
- *Break-Even Point (BEP):* A flexible classifier provides the means to control the tradeoff between precision and recall. For such classifiers, the value of P (and R) satisfying $P = R$ is called the break-even point (BEP). Since it is time consuming to evaluate the exact value of the BEP it is customary to estimate it using the arithmetic mean of P and R.

The above performance measures concern multi-labeled categorization. In a uni-labeled categorization the accepted performance measure is *accuracy*, defined to be the percentage of correctly labeled documents in D_{test}. Specifically, assuming that both $h(d)$ and $\ell(d)$ are singletons (i.e. uni-labeling), the accuracy $Acc(h)$ of h is $Acc(h) = \frac{1}{|D_{test}|}\sum_{d \in D_{test}} I[h(d) = \ell(d)]$. Is it not hard to see that in this case the accuracy equals the precision and recall (and the estimated break-even point).

Following Dumais et al. (1998) (and for comparison with this work), in our multi-labeled experiments (Reuters and 20NG) we report on *micro-averaged break-even point (BEP)* results. In our uni-labeled experiments (20NG and WebKB) we report on *accuracy*. Note that we experiment with both uni-labeled and multi-labeled categorization of 20NG. Although this set is in general multi-labeled, the proportion of multi-labeled articles in the dataset is rather small (about 4.5%) and therefore a uni-labeled categorization of this set is also meaningful. To this end, we follow Joachims (1997) and consider our (uni-labeled) categorization of a test document to be correct if the label we assign to the document belongs to its true set of labels.

In order to better estimate the performance of our algorithms on test documents we use standard cross-validation estimation in our experiments with 20NG and WebKB. However, when experimenting with Reuters, for compatibility with the experiments of Dumais *et al.* we use its standard ModApte split (i.e. without cross-validation). In particular, in both 20NG and WebKB we use 4-fold cross-validation where we randomly and uniformly split each category into 4 folds and we took three folds for training and one fold for testing. Note that this 3/4:1/4 split is proportional to the training to test set size ratios of the ModApte split of Reuters. In the cross-validated experiments we always report on the estimated average (over the 4 folds) performance (either BEP or accuracy), estimated standard deviation and standard error of the mean.

5.2 Hyperparameter Optimization

A major issue when working with SVMs (and in fact with almost all inductive learning algorithms) is parameter tuning. As noted earlier (in Section 3.3), we used linear SVM*light* in our implementation. The only relevant parameters for the linear kernel we use are C (trade-off between training

error and margin) and J (cost-factor, by which training errors on positive examples outweigh errors on negative examples). We optimize these parameters using a *validation set* that consists one third of the three-fold training set.[13] For each of these parameters we fix a small set of feasible values[14] and in general, we attempt to test performance (over the validation set) using all possible combinations of parameter values over the feasible sets.

Note that tuning the parameters C and J is different in the multi-labeled and uni-labeled settings. In the multi-labeled setting we tune the parameters of each individual (binary) classifier independently of the other classifiers. In the uni-labeled setting, parameter tuning is more complex. Since we use the max-win decomposition, the categorization of a document is dependent on all the binary classifiers involved. For instance, if all the classifiers except for one are perfect, this last bad classifier can generate confidence rates that are maximal for all the documents, which results in extremely poor performance. Therefore, a global tuning of all the binary classifiers is necessary. Nevertheless, in the case of the 20NG, where we have 20 binary classifiers, a global exhaustive search is too time-consuming and, ideally, a clever search in this high dimensional parameter space should be considered. Instead, we simply used the information we have on the 20NG categories to reduce the size of the parameter space. Specifically, among the 20 categories of 20NG there are some highly correlated ones and we split the list of the categories into 9 groups as in Table 4.[15] For each group the parameters are tuned together and independently of other groups. This way we achieve an approximately global parameter tuning also on the 20NG set. Note that the (much) smaller size of WebKB (both number of categories and number of documents) allow for global parameter tuning over the feasible parameter value sets without any need for approximation.

Group	*Content*
1	(a) talk.religion.misc; (b) soc.religion.christian (c) alt.atheism
2	(a) rec.sport.hockey; (b) rec.sport.baseball
3	(a) talk.politics.mideast
4	(a) sci.med; (b) talk.politics.guns; (c) talk.politics.misc
5	(a) rec.autos; (b) rec.motorcycles; (c) sci.space
6	(a) comp.os.ms-windows.misc; (b) comp.graphics; (c) comp.windows.x
7	(a) sci.electronics; (b) comp.sys.mac.hardware; (c) comp.sys.ibm.pc.hardware
8	(a) sci.crypt
9	(a) misc.forsale

Table 4: A split of the 20NG's categories into thematic groups.

In IB categorization also the parameter W_{low_freq} (see Section 4), which determines a filter on low-frequency words, has a significant impact on categorization quality. Therefore, in IB categorization we search for both the SVM parameters and W_{low_freq}. To reduce the time complexity we employ the following simple search heuristics. We first fix random values of C and J and then, using

13. Dumais et al. (1998) also use a 1/3 random subset of the training set for validated parameter tuning.
14. Specifically, for the C parameter the feasible set is $\{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}\}$ and for J it is $\{0.5, 1, 2, \ldots, 10\}$.
15. It is important to note that an almost identical split can be computed in a completely unsupervised manner using the Multivariate Information Bottleneck (see Friedman et al., 2001, for further details).

the validation set, we optimize W_{low_freq}.[16] After determining W_{low_freq} we tune both C and J as described above.[17]

5.3 Fair vs. Unfair Parameter Tuning

In our experiments with the BOW+MI and IB categorizers we sometimes perform *unfair* parameter tuning in which we tune the SVM parameters over the *test* set (rather than the *validation* set). If a categorizer A achieves better performance than a categorizer B while B's parameters were tuned unfairly (and A's parameters were tuned fairly) then we can get stronger evidence that A performs better than B. In our experiments we sometimes use this technique to accentuate differences between two categorizers.

6. Categorization Results

We compare text categorization results of the IB and BOW+MI settings. For compatibility with the original BOW+MI setting of Dumais et al. (1998), where the number of best discriminating words k is set to 300, we report on results with $k = 300$ for both settings. In addition, we show BOW+MI results with $k = 15,000$, which is an example for a big value of k that led to good categorization results in the tests we performed. We also report on BOW results without applying MI feature selection.

6.1 Multi-Labeled Categorization

Table 5 summarizes the multi-labeled categorization results obtained by the two categorization schemes (BOW+MI and IB) over Reuters (10 largest categories) and 20NG datasets. Note that the 92.0% BEP result for BOW+MI over Reuters was established by Dumais et al. (1998).[18] To the best of our knowledge, the 88.6% BEP we obtain on 20NG is the first reported result of a multi-labeled categorization of this dataset. Previous attempts at multi-labeled categorization of this set were performed by Schapire and Singer (2000), but no overall result on the entire set was reported.

On 20NG the advantage of the IB categorizer over BOW+MI is striking when $k = 300$ words (and $k = 300$ word clusters) are used. Note that the 77.7% BEP of BOW+MI is obtained using *unfair* parameter tuning (see Section 5.3). However, this difference does not sustain when we use $k = 15,000$ words. Using this rather large number of words the BOW+MI performance significantly increases to 86.3% (again, using unfair parameter tuning), which taking into account the statistical deviations is similar to the IB BEP performance. The BOW+MI results that are achieved with fair parameter tuning show an increase in the gap between the performance of the two methods. Nevertheless, the IB categorizer achieves this BEP performance using only 300 features (word clusters), almost two order of magnitude smaller than 15,000. Thus, with respect to 20NG, the IB categorizer outperforms the BOW+MI categorizer both in BEP performance and in representation efficiency. We also tried other values of the k parameter, where $300 < k \ll 15,000$ and $k > 15,000$. We found

16. The set of feasible W_{low_freq} values we use is $\{0, 2, 4, 6, 8\}$.

17. The "optimal" determined value of W_{low_freq} for Reuters is 4, for WebKB (across all folds) it is 8 and for 20NG it is 0. The number of distinct words after removing low-frequency words is: 9,953 for Reuters ($W_{low\_freq} = 4$), about 110,000 for 20NG ($W_{low\_freq} = 0$) and about 7,000 for WebKB ($W_{low\_freq} = 8$), depending on the fold.

18. This result was achieved using binary BOW representation, see Section 2. We replicated Dumais *et al.*'s experiment and in fact obtained a slightly higher BEP result of 92.3%.

Categorizer	*Reuters (BEP)*	*20NG (BEP)*
BOW+MI $k = 300$	92.0 obtained by Dumais et al. (1998)	76.5 ± 0.4 (0.25) 77.7 ± 0.5 (0.31) unfair
BOW+MI $k = 15000$	92.0	85.6 ± 0.6 (0.35) 86.3 ± 0.5 (0.27) unfair
BOW	89.7	86.5 ± 0.4 (0.26) unfair
IB $k = 300$	91.2 92.6 unfair	88.6 ± 0.3 (0.21)

Table 5: Multi-labeled categorization BEP results for 20NG and Reuters. k is the number of selected words or word-clusters. All 20NG results are averages of 4-fold cross-validation. Standard deviations are given after the "$\pm$" symbol and standard errors of the means are given in brackets. "Unfair" indicates unfair parameter tuning over the test sets (see Section 5.3).

that the learning curve, as a function of k, is monotone increasing until it reaches a plateau around $k = 15,000$.

We repeat the same experiment over the Reuters dataset but there we obtain different results. Now the IB categorizer lose its BEP advantage and achieves a 91.2% BEP,[19] a slightly inferior (but quite similar) performance to the BOW+MI categorizer (as reported by Dumais et al., 1998). Note that the BOW+MI categorizer does not benefit from increasing the number of features up to $k = 15,000$. Furthermore, using all features led to a decrease of 2% in BEP.

Categorizer	*WebKB (Accuracy)*	*20NG (Accuracy)*
BOW+MI $k = 300$	92.6 ± 0.3 (0.20)	84.7 ± 0.7 (0.41) 85.5 ± 0.7 (0.45) unfair
BOW+MI $k = 15000$	92.4 ± 0.5 (0.32)	90.2 ± 0.3 (0.17) 90.9 ± 0.2 (0.12) unfair
BOW	92.3 ± 0.5 (0.40)	91.2 ± 0.1 (0.08) unfair
IB $k = 300$	89.5 ± 0.7 (0.41) 91.0 ± 0.5 (0.32) unfair	91.3 ± 0.4 (0.24)

Table 6: Uni-labeled categorization accuracy for 20NG and WebKB. k is the number of selected words or word-clusters. All accuracies are averages of 4-fold cross-validation. Standard deviations are given after the "$\pm$" symbol and standard errors of the means are given in brackets. "Unfair" indicates unfair parameter tuning over the test sets (see Section 5.3).

19. Using unfair parameter tuning the IB categorizer achieves 92.6% BEP.

6.2 Uni-Labeled Categorization

We also perform uni-labeled categorization experiments using the BOW+MI and IB categorizers over 20NG and WebKB. The final accuracy results are shown in Table 6. These results appear to be qualitatively similar to the multi-labeled results presented above with WebKB replacing Reuters. Here again, over the 20NG set, the IB categorizer is showing a clear accuracy advantage over BOW+MI with $k = 300$ and this advantage is diminished if we take $k = 15,000$. On the other hand, we observe a comparable (and similar) accuracy of both categorizers over WebKB, and as it is with Reuters, here again the BOW+MI categorizer does not benefit from increasing the feature set size.

The use of $k = 300$ word clusters in the IB categorizer is not necessarily optimal. We also performed this categorization experiment with different values of k ranging from 100 to 1000. The categorization accuracy slightly increases when k moves from 100 to 200, and does not significantly change when $k > 200$.

7. Discussion: Corpora Complexity vs. Representation Efficiency

The categorization results reported above show that the performance of the BOW+MI categorizer and the IB categorizer is sensitive to the dataset being categorized. What makes the performance of these two categorizers different over different datasets? Why does the more sophisticated IB categorizer outperform the BOW+MI categorizer (with either higher accuracy or better representation efficiency) over 20NG but not over Reuters and WebKB? In this section we study this question and attempt to identify differences between these corpora that can account for this behavior.

One possible approach to quantify the complexity of a corpus with respect to a categorization system is to observe and analyze learning curves plotting the performance of the categorizer as a function of the number of words selected for representing each category. Before presenting such learning curves for the three corpora, we focus on the extreme case where we categorize each of the corpora using only the *three* top words per category (where top-scores are measured using the Mutual Information of words with respect to categories). Tables 7, 8 and 9 specify (for each corpus) a list of the top three words for each category, together with the performance achieved by the BOW+MI (binary) classifier of the category. For comparison, we also provide the corresponding performance of BOW+MI using the 15,000 top words (i.e., potentially all the significant words in the corpus). For instance, observing Table 7, computed for Reuters, we see that based only on the words "vs", "cts" and "loss" it is possible to achieve 93.5% BEP when categorizing the category *earn*. We note that the word "vs" appears in 87% of the articles of the category *earn* (i.e., in 914 articles among total 1044 of this category). This word appears in only 15 non-*earn* articles in the test set and therefore "vs" can, by itself, categorize *earn* with very high precision.[20] This phenomenon was already noticed by Joachims (1997), who noted that a classifier built on only one word ("wheat") can lead to extremely high accuracy when distinguishing between the Reuters category *wheat* and the other categories (within a uni-labeled setting).[21] The difference between the 20NG and the two other corpora is striking when considering the relative improvement in categorization quality when increasing the feature set up to 15,000 words. While one can dramatically improve categorization

20. In the training set the word "vs" appears in 1900 of the 2709 earn articles (70.1%) and only in 14 of the 4354 non-*earn* articles (0.3%).

21. When using only one word per category, we observed a 74.6% BEP when categorizing Reuters (10 largest categories), 66.3% accuracy when categorizing WebKB and 34.6% accuracy when categorizing 20NG.

of 20NG by over 150% with many more words, we observe a relative improvement of only about 15% and 26% in the case of Reuters and WebKB, respectively.

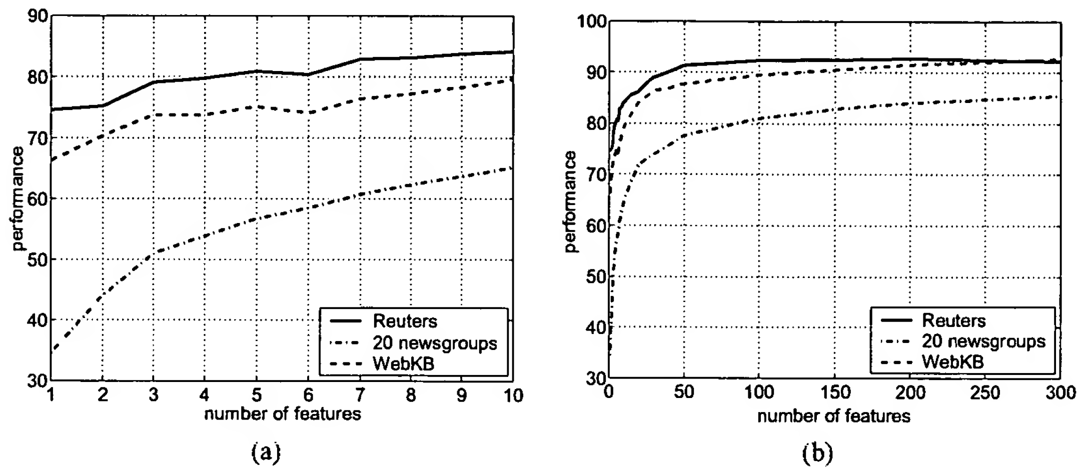

Figure 1: Learning curves (BEP or accuracy vs. number of words) for the datasets: Reuters-21578 (multi-labeled, BEP), 20NG (uni-labeled, accuracy) and WebKB (uni-labeled, accuracy) over the MI-sorted top 10 words (a) and the top 300 words (b) using the BOW+MI categorizer.

Category	*1st word*	*2nd word*	*3rd word*	*BEP on 3 words*	*BEP on 15000 words*	*Relative Improvement*
earn	vs+	cts+	loss+	93.5%	98.6%	5.4%
acq	shares+	vs−	Inc+	76.3%	95.2%	24.7%
money-fx	dollar+	vs−	exchange+	53.8%	80.5%	49.6%
grain	wheat+	tonnes+	grain+	77.8%	88.9%	14.2%
crude	oil+	bpd+	OPEC+	73.2%	86.2%	17.4%
trade	trade+	vs−	cts−	67.1%	76.5%	14.0%
interest	rates+	rate+	vs−	57.0%	76.2%	33.6%
ship	ships+	vs−	strike+	64.1%	75.4%	17.6%
wheat	wheat+	tonnes+	WHEAT+	87.8%	82.6%	-5.9%
corn	corn+	tonnes+	vs−	70.3%	83.7%	19.0%
Average				79.9%	92.0%	15.1%

Table 7: **Reuters:** Three best words (in terms of Mutual Information) and their categorization BEP rate of the 10 largest categories, "+" near a word means that the appearance of the word predicts the corresponding category, "−" means that the absence of the word predicts the category. Words in upper-case are words that appeared in article titles (see Section 4.1).

Category	*1st word*	*2nd word*	*3rd word*	*Accuracy on 3 words*	*Accuracy on 15000 words*	*Relative Improvement*
course	courses	course	homework	79.0%	95.7%	21.1%
faculty	professor	cite	pp	70.5%	89.8%	27.3%
project	projects	umd	berkeley	53.2%	80.8%	51.8%
student	com	uci	homes	78.3%	95.9%	22.4%
Average				73.3%	92.4%	26.0%

Table 8: **WebKB:** Three best words (in terms of Mutual Information) and their categorization accuracy rate of the 4 representative categories. All the listed words contribute by their appearance, rather than absence.

Category	*1st word*	*2nd word*	*3rd word*	*Accuracy on 3 words*	*Accuracy on 15000 words*	*Relative Improvement*
alt.atheism	atheism	atheists	morality	48.7%	84.8%	74.1%
comp.graphics	image	jpeg	graphics	40.5%	83.1%	105.1%
comp.os.ms-windows.misc	windows	m	o	60.9%	84.7%	39.0%
comp.sys.ibm.pc.hardware	scsi	drive	ide	13.8%	76.6%	455.0%
comp.sys.mac.hardware	mac	apple	centris	61.0%	86.7%	42.1%
comp.windows.x	window	server	motif	46.6%	86.7%	86.0%
misc.forsale	00	sale	shipping	63.4%	87.3%	37.6%
rec.autos	car	cars	engine	62.0%	89.6%	44.5%
rec.motorcycles	bike	dod	ride	77.3%	94.0%	21.6%
rec.sport.baseball	baseball	game	year	38.2%	95.0%	148.6%
rec.sport.hockey	hockey	game	team	67.7%	97.2%	43.5%
sci.crypt	key	encryption	clipper	76.7%	95.4%	24.3%
sci.electronics	circuit	wire	wiring	15.2%	85.3%	461.1%
sci.med	cancer	medical	msg	26.0%	92.4%	255.3%
sci.space	space	nasa	orbit	62.5%	94.5%	51.2%
soc.religion.christian	god	church	sin	50.2%	91.7%	82.6%
talk.politics.guns	gun	guns	firearms	41.5%	87.5%	110.8%
talk.politics.mideast	israel	armenian	turkish	54.8%	94.1%	71.7%
talk.politics.misc	cramer	president	ortilink	23.0%	67.7%	194.3%
talk.religion.misc	jesus	god	jehovah	6.6%	53.8%	715.1%
Average				46.83%	86.40%	153.23%

Table 9: **20NG:** Three best words (in terms of Mutual Information) and their categorization accuracy rate (uni-labeled setting). All the listed words contribute by their appearance, rather than absence.

In Figure 1 we present, for each dataset, a learning curve plotting the obtained performance of the BOW+MI categorizer as a function of the number k of selected words.[22] As can be seen, the two

22. In the case of Reuters and 20NG the performance is measured in terms of BEP and in the case of WebKB in terms of accuracy.

curves of both Reuters and WebKB are very similar and almost reach a plateau with $k = 50$ words (that were chosen using the greedy Mutual Information index). This indicates that other words do not contribute much to categorization. But the learning curve of 20NG continues to rise when $0 < k < 300$, and still exhibits a rising slope with $k = 300$ words.

The above findings indicate on a systematic difference between the categorization of the 20NG dataset on the one hand, and of the Reuters and WebKB datasets, on the other hand. We identify another interesting difference between the corpora. This difference is related to the hyper-parameter W_{low_freq} (see Section 4). The bottom line is that in the case of 20NG IB categorization improves when W_{low_freq} *decreases* while in the case of Reuters and WebKB it improves when W_{low_freq} *increases*. In other words, more words and even the most infrequent words can be useful and improve the (IB) categorization of 20NG. On the other hand, such rare words do add noise in the (IB) categorization of Reuters and WebKB. Figure 2 depicts the performance of the IB classifier on the three corpora as a function of W_{low_freq}. Note again that this opposite sensitivity to rare words is observed with respect to the IB scheme and the previous discussion concerns the BOW+MI scheme.

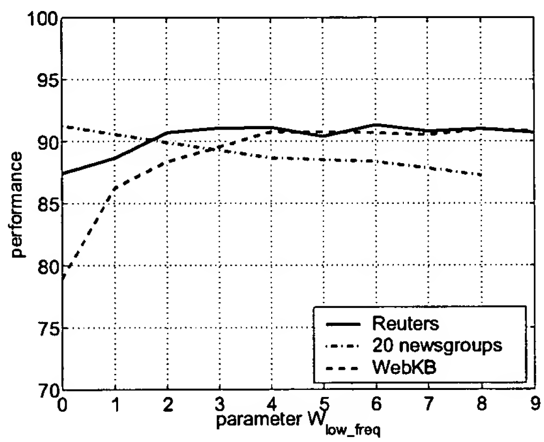

Figure 2: Performance of the IB categorizer as a function of the W_{low_freq} parameter (that specifies the threshold of the low frequency word filter: words appearing in less than W_{low_freq} articles are removed); uni-labeled categorization of WebKB and 20NG (accuracy), multi-labeled categorization of Reuters (BEP). Note that $W_{low\_freq} = 0$ corresponds to the case where this filter is disabled. The number of word clusters in all cases is $k = 300$.

8. Computational Efforts

We performed all our experiments using a 600MHz 2G RAM dual processor Pentium III PC operated by Windows 2000. The IB clustering software, preprocessed datasets and application scripts can be found at:

http://www.cs.technion.ac.il/~ronb

The computational bottlenecks were mainly experienced over 20NG, which is substantially larger than Reuters and WebKB.

Let us first consider the multi-labeled experiments with 20NG. When running the BOW+MI categorizer, the computational bottleneck was the SVM training, for which a single run (one of the 4 cross-validation folds, including both training and testing) could take a few hours, depending on the parameter values. In general, the smaller the parameters C and J are, the faster the SVM training is.[23]

As for the IB categorizer, the SVM training process was faster when the input vectors consisted of word clusters. However, the clustering itself could take up to one hour for each fold of the entire 20NG set, and required substantial amount of memory (up to 1G RAM). The overall training and testing time over the entire 20NG in the multi-labeled setting was about 16 hours (4 hours for each of the 4 folds).

The computational bottleneck when running uni-labeled experiments was the SVM parameter tuning. It required a repetition for each combination of the parameters and individual classifiers (see Section 5.2). Overall the experiments with the IB categorizer took about 45 hours of CPU time, while the BOW-MI categorizer required about 96 hours (i.e. 4 days).

The experiments with the relatively small WebKB corpus were accordingly less time-consuming. In particular, the experiments with the SVM+MI categorizer required 7 hours of CPU time and those with the IB categorizer, about 8 hours. Thus, when comparing these times with the experiments on 20NG we see that the IB categorizer is less time-consuming than the BOW+MI categorizer (based on 15000 words) but the clustering algorithm requires larger memory. On Reuters the experiments ran even faster, because there was no need to apply cross-validation estimation.

9. Concluding Remarks

In this study we have provided further evidence for the effectiveness of a sophisticated technique for document representation using distributional clustering of words. Previous studies of distributional clustering of words remained somewhat inconclusive because the overall absolute categorization performance were not state-of-the-art, probably due to the weak classifiers they employed (to the best of our knowledge, in all pervious studies of distributional clustering as a representation method for supervised text categorization, the classifier used was Naive Bayes).

We show that when Information Bottleneck distributional clustering is combined with an SVM classifier, it yields high performance (uni-labeled and multi-labeled) categorization of the three benchmark datasets. In particular, on the 20NG dataset, with respect to either multi-labeled or uni-labeled categorization, we obtain either accuracy (BEP) or representation efficiency advantages over BOW when the categorization is based on SVM. This result indicates that sophisticated document representations can significantly outperform the standard BOW representation and achieve state-of-the-art performance.

Nevertheless, we found no accuracy (BEP) or representation efficiency advantage to this feature generation technique when categorizing the Reuters or WebKB corpora. Our study of the three corpora shows structural differences between them. Specifically, we observe that Reuters and WebKB can be categorized with close to "optimal" performance using a small set of words, where the addition of many thousands more words provides no significant improvement. On the other hand, the categorization of 20NG can significantly benefit from the use of a large vocabulary. This indicates

23. SVM*light* and its parameters are described by Joachims (1998a).

that the "complexity" of the 20NG corpus is in some sense higher than that of Reuters and WebKB. In addition, we see that the IB representation can benefit from including even the most infrequent words when it is applied with the 20NG corpus. On the other hand, such infrequent words do not affect or even degrade the performance of the IB categorizer when applied to the Reuters and WebKB corpora.

Based on our experience with the above corpora we note that when testing complex feature selection or generation techniques for text categorization, one should avoid making definitive conclusions based only on "low-complexity" corpora such as Reuters and WebKB. It seems that sophisticated representation methods cannot outperform BOW on such corpora.

Let us conclude with some questions and directions for future research. Given a pool of two or more representation techniques and given a corpus, an interesting question is whether it is possible to combine them in a way that will be competitive with or even outperform the best technique in the pool. A straightforward approach would be to perform cross-validated model selection. However, this approach will be at best as good as the best technique in the pool. Another possibility is to try to combine the representation techniques by devising a specialized categorizer for each representation and then use ensemble techniques to aggregate decisions. Other sophisticated approaches such as "co-training" (see, e.g., Blum and Mitchell, 1998) can also be considered.

Our application of the IB distributional clustering of words employed document class labels but generated a *global* clustering for all categories. Another possibility to consider is to generate specialized clustering for each (binary) classifier. Another interesting possibility to try is to combine clustering of n-grams, with $1 \leqslant n \leqslant N$ for some small N.

Another interesting question that we did not explore concerns the behavior of IB and BOW representations when using feature sets of small cardinality (e.g. $k = 10$). It is expected that at least in "complex" datasets like 20NG, there should be an advantage to the IB representation also in this case.

The BOW+MI categorization employed Mutual Information feature selection, where the number k of features (words) was identical for all categories. It would be interesting to consider a specialized k for each category. Although it might be hard to identify good set of vocabularies, this approach may lead to somewhat better categorization and is likely to generate more efficient representations.

In all our experiments we used the simple-minded one-against-all decomposition technique. It would be interesting to study other decompositions (perhaps, using error correcting output coding approaches). The inter-relation between feature selection/generation and the particular decomposition is of particular importance and may improve text categorization performance.

We computed our word clustering using the original top-down (soft) clustering IB implementation of Tishby et al. (1999). It would be interesting to explore the power of more recent IB implementations in this context. Specifically, the IB clustering methods described by El-Yaniv and Souroujon (2001) and Slonim et al. (2002) may yield better clustering in the sense that they tend to better approximate the optimal IB objective.

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